Proceedings of IDETC/CIE 2013
ASME 2013 International Design Engineering Technical Conferences
& Computers and Information in Engineering Conference
Portland OR, USA

DETC2013-12376

RELIABILITY AND FUNCTIONALITY OF REPAIRABLE SYSTEMS USING A MINIMAL SET OF METRICS: DESIGN AND MAINTENANCE OF A SMART CHARGING MICROGRID

Vijitashwa Pandey[1]
pandey2@oakland.edu

Annette Skowronska-Kurec[2]
annette.g.skowronska-kurec.civ@mail.mil

Zissimos P. Mourelatos[1]
mourelat@oakland.edu

David Gorsich[2]
david.j.gorsich.civ@mail.mil

Matthew Castanier[2]
matthew.p.castanier.civ@mail.mil

[1]Mechanical Engineering Department, Oakland University, 2200 N Squirrel Road, Rochester MI 48309
[2]US Army TARDEC, 6501 E. 11 Mile, Rd Warren MI 48397

ABSTRACT

The definition of reliability may not be readily applicable for repairable systems. Our recent work has shown that multiple metrics are needed to fully account for the performance of a repairable system under uncertainty. Optimal tradeoffs among a minimal set of metrics can be used in the design and maintenance of these systems. A minimal set of metrics provides the most information about the system with the smallest number of metrics using a set of desirable properties. Critical installations such as a remote microgrid powering a military installation require a careful consideration of cost and repair strategies. This is because of logistical challenges in performing repairs and supplying necessary spare parts, particularly in unsafe locations. This paper shows how a minimal set of metrics enhances decision making in such a scenario. It enables optimal tradeoffs between critical attributes in decision making, while guaranteeing that all important performance measures are satisfied. As a result, cost targets and inventory planning can be achieved in an optimal way. We demonstrate the value of the proposed approach using a US Army smart-charging microgrid installation.

1. INTRODUCTION

Most real-life engineering systems are repairable. The amount and frequency of repair affects how one perceives their reliability or more generally, their "performance." The classical notion of reliability, defined as the probability that a system has not failed before a given time *t*, can be misleading because it does not account for repairs due to previous failures. The classical reliability definition can also impede decision making involving maintenance, availability and service cost of such systems. Although an appropriate maintenance strategy can make a system available most of the time, it cannot compensate for too many service interruptions and a potentially high service cost. The tradeoffs between performance, service interruptions and cost are hard to capture. Pandey and Mourelatos (2013) have recently shown that we can systematically approach the design and maintenance of repairable systems using a minimal set of metrics (MSOM) to capture most of the information about the working conditions and reparability of such systems. In this paper, we will extend and apply the method to a smart charging electric microgrid (SCMG) used by the US army in remote installations. We will show that the approach can provide a proper repair strategy, including inventory and lifecycle planning. The approach presented here can also be used to augment a common practice the Army employs for managing remote installations, called *reset*[1]. Since such installations are subject to harsh environments and limited maintenance, reset replaces the components by procuring and installing new ones, thereby improving the system or even restoring the system's effective age to zero miles or zero hours returning it to like-new condition. This concept of effective age was developed in Pandey and Thurston (2009) and is used in this paper.

[1] The Army defines reset as: "actions taken to restore equipment to a desired level of combat capability commensurate with a unit's future mission. It encompasses maintenance and supply activities that restore and enhance combat capability to unit and pre-positioned equipment that was destroyed, damaged, stressed, or worn out beyond economic repair ..." (GAO Report GAO-12-133)

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
20 FEB 2013	**Journal Article**	**09-09-2012 to 07-02-2013**

4. TITLE AND SUBTITLE
RELIABILITY AND FUNCTIONALITY OF REPAIRABLE SYSTEMS USING A MINIMAL SET OF METRICS: DESIGN AND MAINTENANCE OF A SMART CHARGING MICROGRID

5a. CONTRACT NUMBER
W56HZV-04-2-0001

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Vijitashwa Pandey; Annette Skowronska-Kurec; Zissimos Mourelatos; David Gorsich; Matthew Castanier

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Mechanical Engineering Department,Oakland University,2200 N Squirrel Road,Rochester,Mi,48309

8. PERFORMING ORGANIZATION REPORT NUMBER
; #23663

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
U.S. Army TARDEC, 6501 East Eleven Mile Rd, Warren, Mi, 48397-5000

10. SPONSOR/MONITOR'S ACRONYM(S)
TARDEC

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
#23663

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
For ASME 2013 International Design Engineering Technical Conferences

14. ABSTRACT
The definition of reliability may not be readily applicable for repairable systems. Our recent work has shown that multiple metrics are needed to fully account for the performance of a repairable system under uncertainty. Optimal tradeoffs among a minimal set of metrics can be used in the design and maintenance of these systems. A minimal set of metrics provides the most information about the system with the smallest number of metrics using a set of desirable properties. Critical installations such as a remote microgrid powering a military installation require a careful consideration of cost and repair strategies. This is because of logistical challenges in performing repairs and supplying necessary spare parts, particularly in unsafe locations. This paper shows how a minimal set of metrics enhances decision making in such a scenario. It enables optimal tradeoffs between critical attributes in decision making, while guaranteeing that all important performance measures are satisfied. As a result, cost targets and inventory planning can be achieved in an optimal way. We demonstrate the value of the proposed approach using a US Army smart-charging microgrid installation.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**	**Public Release**	**9**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

Many approaches exist in the literature to alleviate the issues associated with standard reliability engineering principles when applied to repairable systems. While most reliability texts assume systems to be non-repairable (Kapur and Lamberson, 1977, Haldar and Mahadevan, 1999), there is a significant amount of work in assessing the performance of repairable systems (Rigdon and Basu, 2000). A standard approach uses a statistical *process* instead of a failure time distribution to define the so called power law model, where the inter-failure times are represented by a homogenous Poisson process (HPP) characterizing full repair or by a non-homogenous Poisson (NHPP) process for minimal repair (Crow, 1974 and 2012). Since repaired systems comprise used and new components, the time between failures generally decreases with time. Repairs can often lead to discovery of errors that are subsequently fixed. In such cases, it is possible for the inter-failure time to increase (Wang and Coit, 2005). Consequently, characterizing repairable systems using a statistical process can account for decreasing, increasing or constant inter-failure time allowing us, at least theoretically, to model their performance under various operating and repair strategies.

These methods cannot be used however, in decision making where a decision maker must make tradeoffs between metrics using Pareto fronts (Pandey and Mourelatos, 2013). Pareto (or non-dominated) fronts have been shown to be effective in making decisions over multiple attributes (Deb et al., 2002) if the number of attributes is small.

The paper is organized as follows. Section 2 discusses and presents the minimal set of metrics and the motivation behind them. It also contrasts them with the commonly used metrics of mean time between failures (MTBF) and reliability. Sections 3 and 4 provide a description of the SCMG and the problem formulation for optimal planning, respectively. Section 5 shows the results of a case study. Finally, Section 6 concludes and provides directions for future work.

2. PERFORMANCE OF REPAIRABLE SYSTEMS

Classical reliability theory uses metrics such as MTBF and availability to assess the expected performance of a repairable system. These metrics are calculated using data on times between failures and system repair. The MTBF and availability metrics only capture one statistic of the time between failures (Pandey and Mourelatos, 2013). For example, the MTBF only captures the mean, while availability is simply the ratio of system up-time to the total duration considered. A system that has a skewed distribution of the time between failures will not have its performance well represented by the MTBF only (Figure 1). Similarly, a system that requires constant repair but can be repaired quickly has high availability, but such a system has little practical use, as it is hard to get any meaningful service out of it. Section 2.1 shows that we can describe the performance of a repairable system very effectively with a carefully chosen set of metrics.

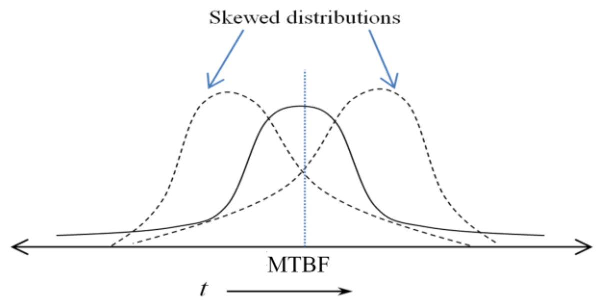

Figure 1. MTBF represents the expected time between failures correctly only for symmetric distributions (solid line)

2.1 Minimal set of metrics

A minimal set of metrics (MSOM) is defined in this section for describing the performance of a repairable system. The set of metrics, individually or together, should cover most aspects of a repairable system performance. To accomplish this, we use the following set of desirable properties (desiderata).

1. The MSOM should be able to describe the performance of a repairable system when it is first installed with all new components.
2. The MSOM should also be able to describe the performance of a repairable system when it has undergone a few repair and installation cycles.
3. The MSOM should show how often repairs are required for the system.
4. The MSOM should be usable for a fleet of systems where the end-user selects one system from the fleet at an arbitrary time and expects a certain performance level or a trouble-free mission length.
5. Because performance comes at a cost, the MSOM should be able to quantify this tradeoff.
6. Aside from functional loss, there is always the issue of technical obsolescence. The MSOM should be able to account for this.
7. The MSOM should identify, to a fair degree of accuracy, the best repair strategy for system maintenance.
8. The MSOM should indicate how long the system will be in operation, even with constant repair, before being replaced by a new technology.

Table 1 lists the metrics in our proposed MSOM which collectively meet the desired properties.

Table 1. Metrics comprising the MSOM

Metric	Description
Minimum failure free period (MFFP) with probability p (T_p)	Since MFFP is specified with a given probability, it only provides one statistic of time to failure. Two different MFFPs (transient and steady-state) can resolve the issue.
Planning horizon (P)	It specifies the total duration over which the system is maintained. It provides a benchmark for other metrics.
Number of failures within the planning horizon (N_f)	Over a planning horizon, the number of failures is a useful metric of system performance.
Effective age ($\bar{t}$)	Age of a system in years, considering technical obsolescence and physical reliability.
Repair time (t_r)	The amount of time to take the system offline and perform repairs.
Cost (c_r)	Cost of commissioning and performing maintenance on the system over the planning horizon.

As noted in the table, we separate T_p into two constituents; the transient (or initial) MFFP, T_P^0, and the steady-state MFFP, T_P^S.

It can be easily verified that the MSOM satisfies all the desiderata. For example, T_P^0 and T_P^S address desiderata 1, 2, 3 and 4, P addresses desideratum 8, N_f addresses desiderata 2, 3 and 4, $\bar{t}$ addresses 2, 3, 4, 6 and 7, t_r addresses desideratum 7 and c_r addresses 5. While most of the metrics satisfy multiple desiderata they also have significant overlap with each other. We report the full set of MSOM when describing performance however, because of subtle differences between them. For example, T_P^0 and T_P^S implicitly model the repair frequency but N_f is a more direct measure. Together they can give a proper description of how many repairs are required and what is the inter-repair time. Similarly, while $\bar{t}$ captures multiple desiderata, it measures performance at an instant in time and is limited in measuring performance over the whole planning horizon. Therefore, we need the overlap. Devising metrics simply to minimize overlap may be counterproductive.

While most of the metrics are self-explanatory, we provide here a brief explanation of the effective age. The metric was first proposed by Pandey and Thurston (2009) to show how the performance of remanufactured (or repaired) systems can be reported in units of time, called effective age. The concept of effective age is a rigorous way of implementing *reset*, as defined in Section 1.

Let us consider a system with n components, with reliability functions $R_i(t_i),\ \ i = 1,\dots,n$. A functional $F(.)$ combines the component reliabilities to give the reliability of the system. For example, for a series system, $F(.)$ is simply the product of its arguments. The system failure modes are therefore, embedded in F. The system reliability $R(t_i,..t_n)$ is

$$R(t_i,..t_n) = F\left(R_i(t_i),..R_n(t_n)\right). \tag{1}$$

When all components have the same age, the system reliability $R^S(t)$ is denoted by

$$R^S(t) = F\left(R_i(t),..R_n(t)\right). \tag{2}$$

The effective age $\bar{t}$ of a system with components of different ages, is the provided by Equation (3) as

$$\bar{t} = R^{S^{-1}}\left(F\left(R_i(t_i),\dots,R_n(t_n)\right)\right). \tag{3}$$

This definition compares therefore, the system reliability with that of a system that has never required repair and reports the corresponding effective age. For a repaired system, the user can assess if it would provide acceptable service in the future based on how old the individual components are. The effective age metric quantifies this assessment by comparing the repaired system with one that is in working condition and has never been disassembled and repaired. Thus, the effective age approach avoids a mathematical definition of reliability and uses instead easily relatable units of time. Also, it implicitly captures the obsolescence in the system as a function of time, particularly if the subjective opinions are built into the effective age. The reader is referred to Pandey and Thurston (2009) for a detailed treatment of the topic.

In most cases, first order approximations can be used to simplify the calculation of the effective age $\bar{t}$. Let us consider the linear approximation of increments in $\bar{t}$ as a function of increments in individual t_i's. Using partial derivatives with respect to t_i's we have

$$d\bar{t} = \frac{\partial \bar{t}}{\partial t_1} dt_1 + \frac{\partial \bar{t}}{\partial t_2} dt_2 + \ldots + \frac{\partial \bar{t}}{\partial t_n} dt_n \,. \quad (4)$$

The partial derivatives represent the criticalities of the corresponding components. They can be used to directly approximate $\bar{t}$ if its value is known for nearby values of t_i's. This simplifies the calculation of $\bar{t}$ computationally. Pandey and Thurston (2009) showed that the sum of criticalities is equal to one if all components are of the same age. The computational effort to estimate the change in $\bar{t}$ using the linear approximation of Equation (4) is therefore, very small. The equation can be used to quickly estimate the effective age if minor upgrades are made to the system. The criticality information can also be helpful in determining which component we should expend energy and effort on to improve the system performance.

3. THE SMART CHARING MICROGRID

A smart charging microgrid (SCMG) is used in remote locations to provide reliable power to critical installations. The SCMG we consider in this paper takes power from four distinct sources: utility mains, solar array, backup generators and vehicle batteries. Figure 2 shows the schematic of the SCMG.

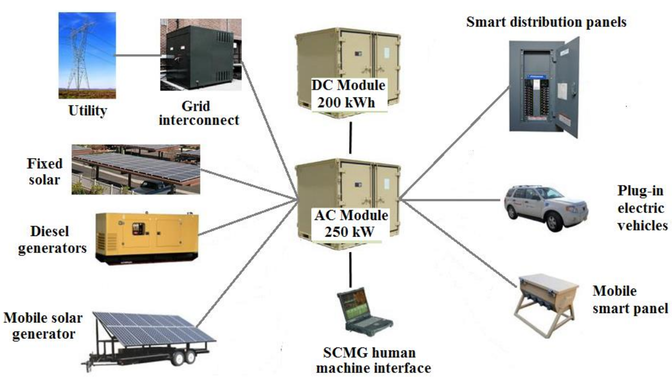

Figure 2. A smart charging microgrid

The grid incorporates intelligent power management to enable a robust and reliable microgrid in order to offer substantial fuel and maintenance economies over its service life. We developed a MATLAB simulation model which can represent both continuous and discrete events, such as time varying loads and generator starts/stops and breaker trips or grid faults.

The smart grid consists of the following modules:

1. An AC module which manages power conditioning and distribution for connection to the public utility grid, two diesel generators and 25 kW photovoltaic solar arrays.
2. A DC module which employs enough stored energy in the batteries to charge the four e-vehicles at the location, twice over. It can accept charging power from the 480 volt AC sources. It can also supply power to the local grid in the event that all other AC sources become unavailable.

Simplified problem

To fully demonstrate our approach, we simplified the SCMG design and maintenance problem. We only consider the sources and related contactors in the SCMG. This reduces the complexity of the problem only marginally while allowing us to demonstrate the different aspects of design and maintenance. The SCMG source system is assumed to include the following components:

1. Utility mains (300 kW line)
2. Two 150 kW diesel generators
3. Two 25 kW solar arrays, and
4. Five contactors; one for each of the above sources.

These sources are all connected in parallel and can provide power to the grid if the contactor is on. However, they are not completely redundant. If the sum of the power provided by the sources is not enough to power all loads, the system is considered failed. Five contactors are therefore, used; one for the utility and two each for the diesel generators and the solar arrays. To avoid delay in repair and maintenance, spares of these components (except the utility) are kept. This results in a tradeoff between easier upkeep and procurement and inventory costs for these components. Figure 3 shows the simplified system.

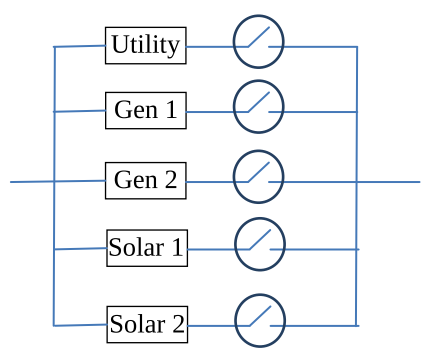

Figure 3. Schematic of the SCMG source system

The sources are given priority numbers which determine the reverse order in which they will be taken offline if necessary. A low number indicates that the source is critical and will be taken offline after the other sources have already been taken offline. The load side of the SCMG is not explicitly modeled. However, loads are shed and added depending on the system's excess capacity. Three loads are considered: building loads, battery charging loads, and other miscellaneous loads. Each load also has a priority number. Table 2 shows the priority numbers for the sources and loads.

Table 2. Priority numbers of sources and loads

SOURCES		LOADS	
Type	**Priority number**	**Type**	**Priority number**
Utility	1	Building	1
Generator 1	2	Battery charging	2
Generator 2	3	Other loads	3
Solar array 1	4		
Solar array 2	5		

Source and load characteristics

Details for the power sources and loads are provided below in terms of their power generation/consumption.

Utility mains: The utility connection is assumed to have a 99% availability. The total power that can be drawn is 300 kilowatts before the supply trips. Assuming six hour failure durations, utility fails about 14 times in a year. This leads to an MTBF of about 625 hours.

Generators: The generators are 100 kilowatt units with an MTBF of 500 hours. The replacement time is 8 hours if a generator is available in the inventory. Otherwise, it is 72 hours, including procurement from a remote location.

Solar arrays: The two solar arrays are 25 kilowatts each. They include batteries and an inverter unit. They are able therefore, to provide constant power during day and night. The commonly used inverter units have MTBFs in the range of hundreds of years. Thus, we do not consider them because their reliability does not affect the reliability of the array and hence the microgrid. Similarly to the generators, the replacement time is 8 hours if a backup solar array is available in the inventory; otherwise it is 72 hours.

Building loads: The building is the main load to be serviced. The load is cyclic because of the difference in power consumption during work hours and at night. The consumption is assumed to be a sine wave with a 350 kW amplitude and a period of one day.

Battery charging: The batteries require a constant charging power of 125 kW. They include the batteries in the solar arrays, the e-vehicle batteries and the batteries of emergency power units which are not considered explicitly in this paper.

Miscellaneous loads: Other miscellaneous loads may include powering of outside equipment as well as external lighting in the complex. We assume them to be normally distributed with a mean of 50 kW and a standard deviation of 10 kW.

Table 3 provides the baseline MTBF in hours of operation and the baseline cost for each component. The MTBF is an indicator of reliability but is not directly used in our simulation. The time between failures of each component is assumed to follow a Beta distribution with an upper limit equal to four times the MTBF.

Table 3. Mean time between failures (MTBF) of the components used in the microgrid

Component	MTBF	Unit Cost
Contactor	2000 hours	$2,000
25 kW solar array	219,000 hours	$70,000
100 kW Diesel Generator	500 hours	$51,800
Utility 300 kW line	625 hours	/KWh

Power Management

The SCMG implements control by sensing power usage at various loads and routing power to and from several system components to bring the system to the desired state of operation. This entails switching contactors on or off. In our MATLAB simulation, the contactors are modeled as switches that respond to the state of a Boolean variable (enable, 0 or 1). Some states are 'hardwired' to be mutually exclusive.

When initiated, the grid starts at the system equilibrium and remains in this state unless/until the excess system capacity moves outside specified set-points. Excess capacity is defined as the available power in excess of the current load, and is expressed as the following percentage

$$C_{excess} = \frac{(Source - Load)}{Load} \cdot 100\% \ . \tag{5}$$

4. PROBLEM FORMULATION AND RESULTS

Here we demonstrate how our proposed minimal set of metrics can be used in decision making for the design and maintenance of the SCMG. We first discuss the mathematical formulation and then present results derived from running the model.

Table 4 provides our notation for the microgrid optimization problem.

Table 4. Notation for microgrid optimization

Symbol	Description	Symbol	Description
P_{source}	Total power available from online sources	n_{gen}	Number of selected generators
P_{load}	Total power required by online loads	n_{solar}	Number of solar panels
C_{excess}	Percentage of excess power available over load	$n_{breakers}$	Number of circuit breakers (installed plus backup)
ns_{total}	Total number of available sources	n_{batt}	Number of batteries in the DC module
ns_{online}	Total number of online sources	P	Length of planning horizon
nl_{total}	Total number of available loads	$\bar{t}_{\max}$	Maximum allowed effective age
nl_{online}	Total number of online loads	N_f	Number of failures within planning horizon
t_f	Time at which failure occurs	$T^i_{working}$	The i^{th} failure free period

Problem formulation

The SCMG must be maintained for 1 year; i.e. P=365x24 hours. During this period, the SCMG goes through many cycles of failure and repair. A failure is defined as the period where the online sources are not able to meet the load requirements. This can happen because of insufficient installed capacity or because of component failures. As discussed before, the loads are stochastic and as such, we do not know their exact value at a particular time. Even though loads are shed (in the reverse order of priority precluding thereby, a complete failure of the grid) any shedding is counted as a failure. Sources and loads are added and removed at other times also. If the load requirements are too low, some sources are shed to save fuel and also to increase reliability by decreasing up-time. We assume that the increase in reliability is more significant than the potential harm from frequent turning on and off the sources. In systems where the opposite is true, sources can be kept on all the time. In this study, we do not consider this scenario.

If the load gets too close to the total supply, either sources are added or loads are shed or both. The following set points, acting as decision variables, are used:

1. If the system excess capacity falls below s_{so}, any additional sources that are available will be brought online.
2. If the system excess capacity increases beyond s_{ss}, sources will be moved to 'standby' status according to their sequence ranking, to conserve fuel and minimize runtime, minimizing therefore, maintenance costs and downtime.
3. If the system excess capacity falls below s_{ls} loads will be shed in the reverse order of their ranking.
4. If the system excess capacity exceeds s_{lo}, loads that were taken offline before will be brought online again.

Figure 4 shows the power management protocol based on the above four set points. The protocol enables the microgrid to revert to a state where all loads are powered if enough supply is available. This guarantees that given sufficient capacity, the operation of the microgrid regains equilibrium (all loads are online) starting from any state. This does not imply however, that failures will not happen. It only implies that if enough capacity is available, the protocol can bring the system back to an operational status from a failure.

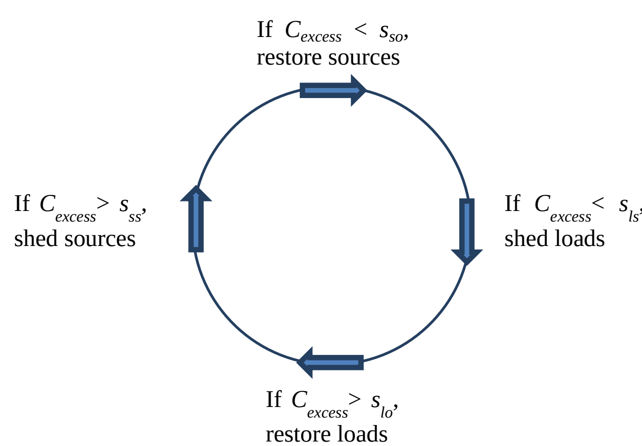

Figure 4. Power management protocol for microgrid

If all loads are online and are powered by available sources, the system is considered operational. Otherwise, it has failed. As mentioned before, failure occurs for two reasons:

1. The system does not have enough installed capacity to power all loads at all times.
2. Some or all of the components have failed and despite having enough capacity some loads are not being powered.

The first scenario requires waiting until the load requirements go down and the system starts working again. The second scenario requires repair of the malfunctioning components. We denote the online loads and total online sources with $P_{loads}(t)$ and $P_{sources}(t)$, respectively. Both are stochastic processes indexed in time. Failure happens at time t_f if

$$\{P_{source}(t_f) - P_{load}(t_f) < 0 \cup nl_{online}(t_f) < nl_{total}(t_f)\}. \quad (6)$$

The number of failures within the planning horizon (i.e., the number of *different* times $t = t_f$ failure has occurred) is given by N_f. A running repository of $T_{working}$ is also kept in order to calculate $T_{0.8}$ (see Table 1) using the CDF $F_{T_{working}}(t_{working})$.

The following multiobjective optimization problem is solved using the NSGA-II multiattribute genetic algorithm (Deb et al., 2002) which uses many randomly generated starting points.

$$\underset{\mathbf{x}}{Min}\{-T_{0.8}, N_f, C\} \quad (7)$$

where:

$$\mathbf{x} = \{s_{ls}, s_{so}, s_{lo}, s_{ss}, n_{gen}, n_{solar}, n_{contacts}\}^T$$

$$T_{0.8} = F^{-1}_{T_{working}}(0.2)$$

$$C = C_{initial} + C_{repair}$$

subject to:

$$g_1(\mathbf{x}): P = 8760,\ g_2(\mathbf{x}): \bar{t}_{\max} \le 2000$$

$$n_{gen}, n_{solar}, n_{contacts}, n_{batt} \in N$$

$$s_{ls}, s_{so}, s_{lo}, s_{ss}, \in [0,100]$$

The problem involves simultaneous maximization of the MFFP and minimization of the number of failures and cost. Other metrics which affect the optimal solution are considered as constraints. For example, the effective age must remain below 2000 hours while the planning horizon is fixed at 8760 hours (365 days; i.e., 1 year). The design variables include the set points $s_{so}, s_{ss}, l_{lo}, l_{ls}$ for restoring and shedding sources and loads as well as the number of sources and breakers $n_{gen}, n_{solar}, n_{breakers}$ at the beginning of the installation. Sources and breakers that are not used are stored in the inventory. Thus, this formulation automatically accounts for the inventory size, repair time and their impact on the MSOM.

Implementation

A MATLAB suite of programs was developed comprising two modules; the optimization module and the simulation module. The former uses the NSGA-II multiattribute genetic algorithm to identify the best combinations of design variables to simultaneously optimize the three objectives of Equation (7). For each set of design variables, the simulation module tracks all loads for 8760 hours at one-hour intervals. Then the simulation module uses the values of s_{so}, s_{ss}, l_{lo} and l_{ls} in the design variable vector to decide whether to add or shed loads and/or sources. The simulation module keeps track of when failures occur and how long they last. If a particular failure requires replacement of a component, the module takes into account the replacement delay and the associated cost. The cost is then added to the initial cost of installation. The simulation module finally reports the cost, the 20th percentile of time between failures ($T_{0.8}$) and the number of failures within the planning horizon to the optimizer which in turn compares it with other solutions and ranks it within the GA population. All solutions are then evolved until a good approximation of the Pareto front over the three attributes is found.

Results

Figure 5 shows one realization of the load profile for a 3-day (72 hours) duration. The load profile is the sum of the three types of loads: building, charging and miscellaneous. The figure also shows the five sources (see Table 2) which are incrementally added according to their priority, and the relative magnitudes of the load and all sources, indicating that peak loads can be met if all sources are online (contactors are on) and the sources themselves are operational.

Based on Figure 5, a few observations can be made. For example, during off peak hours, the utility is enough to power all loads. Similarly, the utility and the generators together can power all loads most of the time. An optimal power management strategy will only keep the minimal number of sources online to save money and protect components, with a small margin of safety so that sudden load spikes can be dealt with. During optimization, our simulation algorithm sequentially adds and removes sources and loads if necessary, to ensure that the supply exceeds the load. If there are component failures, either because the sources cannot be brought online due to contactor failures or failure of the sources themselves, it may be impossible to balance supply and load. Such a scenario constitutes a system failure.

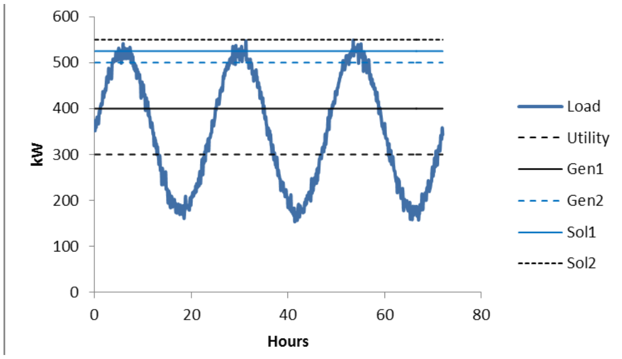

Figure 5. Microgrid load and source profiles for a period of 3 days (72 hours)

Figure 6 shows the Pareto front generated over the three attributes of mean failure free period (MFFP) represented by $T_{0.8}$, the number of failures N_f and the cost C. Each point on the front shows a different tradeoff between the three attributes. As discussed before, the metrics of planning horizon and effective age are used as constraints and are not explicitly appear on the Pareto front.

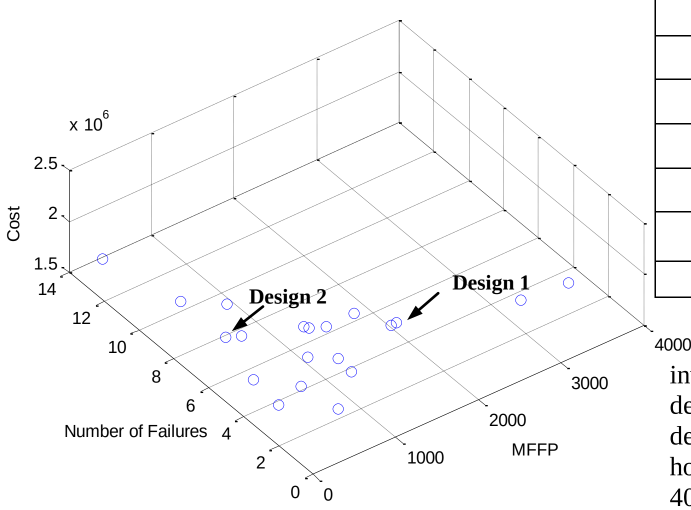

Figure 6. Pareto front over MFFP, number of failures and cost

The Pareto front is presented to a decision maker who chooses a design based on his/her tradeoff preferences. Table 5 shows two different designs on the Pareto front. Design 1 provides a longer MFFP (with 80% probability) at a higher cost with lesser failures within the planning horizon compared to design 2. The advantages provided by design 1 in MFFP and number of failures, are significant for only a marginal increase in cost. Therefore, it is likely to be preferred by most decision makers. Based on the set point l_{ls} for shedding loads, the loads are shed very late for design 2, when they are only 0.2% below the sources. This increases the probability of failure from sudden increase in load since load and sources are very close to each other.

Design 2 also sheds sources early, at only 27.4% above the load in order to save money and to extend the life of the components. This is detrimental however, since instantaneous load spikes cannot be met as some of the sources were taken offline. The low values of both l_{ls} and s_{ss} result in a higher number of failures for design 2 compared to design 1 within the planning horizon.

Table 5. Decision variables and corresponding attributes for two designs on the Pareto front

Decision variables	Design 1	Design 2
l_{ls}	14.0 %	0.2 %
s_{so}	20.2 %	13.7 %
l_{lo}	30.6 %	16.8 %
s_{ss}	37.1 %	27.4 %
n_{gen}	5	4
$n_{contacts}$	12	19
n_{solar}	3	3
Attributes		
$T_{0.8}$	1516.1 hrs	403.1 hrs
N_f	2	7
C	2.061 M	1.967 M

Another important observation is that design 1 invests in one more generator (5 for design 1 versus 4 for design 2) while design 2 invests in contactors (19 for design 2 versus 12 for design 1). As a result, the 1516.1 hour MFFP for design 1 is substantially higher than the 403.1 hour MFFP of design 1. Recall that the generator repair time is long at about 8 hours and even longer (72 hours) when it is not available in the inventory and must be procured from a remote location. A quick replacement also ensures that the generator is back online quickly so that a potential failure of another component when the generator is offline does not result in a grid failure. This leads to a lower number of failures for design 1.

Note that Table 5 only shows the initial component count and not the count during the whole planning horizon after replacements. This initial count still leads to lower procurement delays (one less generator must be procured) and a higher MFFP.

We should note that the results from our method are not directly comparable with results from standard reliability engineering methods. This is because of the fundamental challenges one faces when implementing classical reliability methods on repairable systems as outlined in Section 1.

5. SUMMARY AND CONCLUSIONS

In this paper, we developed metrics to describe the performance of repairable systems and showed how they can be used in decision making. Many systems are repairable but classical reliability theory, while very powerful, may not be able to provide a complete description of their performance. The well-known metrics of MTBF and availability provide only limited information for a repairable system. Furthermore, it is very hard to make tradeoff decisions for repairable systems if a statistical process such as the homogeneous or non-homogeneous Poisson process is used to model their inter-failure times.

We advocated in this paper that it is desirable to deduce as much about the performance of repairable systems as possible by using as few metrics as possible. For that, we created a set of desirable properties on the characteristics of repairable systems we want to measure their performance with. We showed how a minimum set of metrics (MSOM) can be used as attributes in a design optimization process to obtain a set of Pareto optimal designs which can be then presented to a decision maker to select the best design according to his/her preferences. The operation and maintenance of a smart charging microgrid was used to demonstrate the approach.

Our results showed that critical systems such as a remotely located microgrid can be optimally designed and maintained using the MSOM. In future work, we plan to tailor the MSOM for different applications which might require adding or removing metrics from the set. We believe that our approach adds significant value to the literature on repairable systems.

ACKNOWLEDGMENT

We would like to acknowledge the technical and financial support of the Automotive Research Center (ARC) in accordance with Cooperative Agreement W56HZV-04-2-0001 U.S. Army Tank Automotive Research, Development and Engineering Center (TARDEC) Warren, MI.

REFERENCES

1. Crow, L. H., 2012, http://www.reliasoft.com/newsletter/v5i1/repairable.htm, Date Accessed 11/10/2012.
2. Crow, L.H., 1974, *Reliability Analysis for Complex, Repairable Systems in Reliability and Biometry*, eds F. Proschan & R.J. Serfing, SIAM, 379-410, Philadelphia.
3. Deb, K., Pratap, A., Agrawal, S., and Meyarivan, T., 2002, “A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II,” *IEEE Transactions on Evolutionary Computation*, 6(2), 182–197.
4. GAO Report, GAO-12-133, http://www.gao.gov/assets/600/590873.pdf, Date Accessed 4/10/2013.
5. Haldar, A. and Mahadevan, 1999, *Probability Reliability and Statistical Methods in Engineering Design*, 1st Edition, John Wiley and Sons.
6. Kapur, K.C. and Lamberson, L. R., 1977, *Reliability in Engineering Design*, 1st Edition, John Wiley and Sons.
7. Mourelatos, Z. P., Li, J., Pandey, V., Singh, A., Castanier, M. and Lamb, D., 2011, “A Simulation and Optimization Methodology for Reliability of Vehicle Fleets,” *SAE International Journal of Materials and Manufacturing*, 4(1), 883-895.
8. Pandey, V. and Thurston, D., 2009, “Effective Age of Remanufactured Products: An Entropy Approach,” *ASME Journal of Mechanical Design*, 131(3), 031008 (9 pages).
9. Pandey, V. and Mourelatos, Z. P., 2013, “New Metrics to Assess Reliability and Functionality of Repairable Systems,” *SAE World Congress*, Paper 2013-01-0606, Detroit, MI.
10. Rigdon, S. and Basu, A., 2000, *Statistical Methods for the Reliability of Repairable Systems*¸ 1st Edition, Wiley-Interscience, pp. 224.
11. Wang, P. and Coit, D.W., 2005, “Repairable Systems Reliability Trend Tests and Evaluation” *Proceedings of the Annual Reliability and Maintainability Symposium*, 416 – 421.